Title

Representing decision-makers using styles of behavior: an approach designed for group decision support systems

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Abstract

Supporting decision-making processes when the elements of a group are geographically dispersed and on a tight schedule is a complex task. Aiming to support decision-makers anytime and anywhere, Web-based Group Decision Support Systems have been studied. However, the limitations in the decision-makers' interactions associated to this scenario bring new challenges. In this work, we propose a set of behavioral styles from which decision-makers' intentions can be modelled into agents. The goal is that, besides having agents represent typical preferences of the decision-makers (towards alternatives and criteria), they can also represent their intentions. To do so, we conducted a survey with 64 participants in order to find homogeneous operating values so as to numerically define the proposed behavioral styles in four dimensions. In addition, we also propose a communication model that simulates the dialogues made by decision-makers in face-to-face meetings. We developed a prototype to simulate decision scenarios and found that agents are capable of acting according to the decision-makers' intentions and fundamentally benefit from different possible behavioral styles, just as a face-to-face meeting benefits from the heterogeneity of its participants.

Keywords

Group Decision Support Systems, Styles of Behavior, Cognitive Agents, Affective Computing

1. Introduction

It is a given that in organizations most decisions are group decisions (Lunenburg, 2011). There are 2 main reasons: on the one hand, most of the current organizations organigrams involve several decision-makers (Luthans, 2010), both at the strategic (Eisenhardt & Zbaracki, 1992) and at the technical level (Montoya-Weiss, Massey, & Song, 2001), and on the other hand, deciding as a group can potentiate the decision quality (Dennis, 1996; Hill, 1982; Huber, 1984).

Group Decision Support Systems (GDSS) have been widely studied throughout the last decades (DeSanctis & Gallupe, 1984, 1987; Gray, 1987; Marakas, 2003) to support this type of decisions. However, in the last ten/twenty years, we have seen a remarkable change in the context where the decision-making process happens, particularly in large organizations (Chen, Liou, Wang, Fan, & Chi, 2007; Grudin, 2002). With the emergence of global markets, the growth of multinational organizations and a globalist view of the planet, we can easily have decision-makers (chief executive officers, managers and other members of global virtual teams) spreading around the world, across countries with different time zones (Shum, Cannavacciuolo, De Liddo, Iandoli, & Quinto, 2013). Moreover, to support the group decision-making process in this context is particularly complex, due to the decision-makers being geographically dispersed. This can lead to additional problems: failure to communicate and retain contextual information, unevenly distributed information, difficulty to communicate and to understand the salience of information, differences in the speed of access to information, and difficulty to interpret the meaning of silence (Bjørn, Esbensen, Jensen, & Matthiesen, 2014); and to deal with temporal issues, which can originate: ambiguity, conflicting temporal interests and requirements, and scarcity of temporal resources (McGrath, 1991). To provide an answer and operate correctly in this type of scenarios, the traditional GDSS have evolved to what we identify today as Web-based GDSS (Alonso, Herrera-Viedma, Chiclana, & Herrera, 2010; Kwon, Yoo, & Suh, 2005; Marreiros, Santos, Ramos, & Neves, 2010). The idea behind the Web-based GDSS is to support the decision-making process "anytime" and "anywhere" (Santos, Marreiros, Ramos, Neves, & Bulas-Cruz, 2006; Shim et al., 2002), and to help deal with some of the referred problems. Two main approaches have been implemented in GDSS to help with group decision-making processes. The classical approaches, based on preferences' aggregation, and the consensus-based approaches. The former consists in an aggregation phase, that combines the experts' preferences, followed by the selection of one alternative (Herrera, Martınez, & Sánchez, 2005; Saaty, 1988). The latter extends the former through an iterative process in order to achieve consensus (Fedrizzi & Kacprzyk, 1988; Iván Palomares & Martínez, 2014b).

When developing a Web-based GDSS it is necessary to be aware of the benefits inherent to group decision-making. A typical face-to-face meeting allows the decision-makers' interaction, exchange of ideas, work on new knowledge and intelligence generation (Dennis, 1996; Hill, 1982; Huber, 1984). In an ideal scenario, we can achieve some of these benefits using automatic negotiation models (for instance: argumentation-based negotiation models). However, there is much more besides the "messages" exchanged by decision-makers. It is necessary to work in the representation of those decision-makers. The representation can range from criteria's evaluation (for instance in a multi-criteria problem (Carneiro, Martinho, Marreiros, & Novais, 2015)) to a complete representation of the individual (personality, emotions, mood, etc. (Gmytrasiewicz & Lisetti, 2002; Raja & Srivatsa, 2006; Santos, Marreiros, Ramos, Neves, & Bulas-Cruz, 2009b)). The face-to-face meetings benefit from the decision-makers' heterogeneity (Hambrick, Cho, & Chen, 1996). This heterogeneity is related with the decision-makers' temperament but also with the decision-makers' intentions. Let us consider a scenario in which a medical team intends to choose a particular course of treatment for a patient whose condition calls for different areas of expertise. As in any other multi-criteria problem, each of the specialists, depending on their own background could have their own preferences over a number of possible alternatives, considering for instance, the order/timing of certain required interventions. However, each team member's opinion may be subject to a different appreciation, being judged for instance in terms of importance, rank, expert level or even based on implicit rules regarding their overall credibility. It is also conceivable that in some authoritative contexts the opinions of the highest graduated specialist may be taken as the rule of law, limiting any further suggestions once they are stated.

To model agents with human-like aspects is not new. At the start of the new millennium, some projects dealing with agents' humanization began to appear (André, Klesen, Gebhard, Allen, & Rist, 2000). Nowadays, there are many proposals that intend to model human characteristics in agents, such as: personality (Dimuro, da Rocha Costa, Gonçalves, & Hübner, 2007; Padgham & Taylor, 1997), emotions (Ball & Breese, 2000; Gmytrasiewicz & Lisetti, 2002), cognitive styles (Frank, Bittner, & Raubal, 2001), etc. There are also some few proposals under the topic of GDSS (Ivan Palomares, Martinez, & Herrera, 2014; Iván Palomares, Rodríguez, & Martínez, 2013; Recio-García, Quijano, & Díaz-Agudo, 2013; Santos et al., 2009b). All of them share the idea that the inclusion of cognitive/affective aspects helps in some way the decision-making process. However, (to the best of our knowledge) most of them are oriented to be used in simulated environments. The usage of such techniques in real systems can bring some disadvantages. "A real me" can be a bad approach if my persona is less persuasive/intelligent/capable than others. An application that mimics one's limitation will be of lesser interest. Moreover, the inclusion of aspects such as personality, do not permit to reflect other aspects such as intentions and objectives. For each decision-maker the objectives and intentions can vary even for the same problem.

In this article, we propose a set of behavioral styles (Dominating, Integrating, Compromising, Obliging and Avoiding) to model agents that represent decision-makers in a group decision-making process. An agent modelled with each of these behavior styles is able to act following the intentions of the decision-maker it represents; The intentions may be for instance "preferring to please a group of other decision-makers", "preferring to dominate the course of the decision", "let people better positioned to lead the decision process", etc. The proposed behavioral styles act according to four dimensions deemed relevant in the context of group decision-making (Concern for self, Concern for others, Resistance to change and Activity level). Moreover, we introduce a communication model that allows agents to have dialogues that mimic the logic of communication existing in face-to-face meetings. Our research hypotheses are: (h1) it is possible for decision-makers to select behavioral styles to model computer agents in the context of group decision-making so that the behavior of the agents is as expected by the decision-makers; (h2) computer agents can act according to the style of behavior with which they are defined; (h3) a cooperative decision system that uses agents modelled with behavioral styles should be able to benefit from this heterogeneity and not present a biased functioning. In order to study h1, we carried out a survey with 64 participants to understand if the definition of the proposed behaviors has a homogeneous understanding on the part of the users and more importantly to find a homogeneous classification (numeric) of the behavioral styles in the proposed dimensions. To study h2 and h3, we have developed a prototype of a multi-agent system that includes a previously proposed argumentation-based negotiation (ABN) model for running simulations. In the developed prototype, the agents try to achieve the consensus through an iterative process (the ABN model used is fully described in Carneiro, Martinho, Marreiros, Jimenez, and Novais (In Press, 2017)). We created different simulation environments with different numbers of agents in order to study the hypotheses. The proposed behavioral styles, as well as the proposed definitions, allowed us to find homogeneous operating values in the proposed dimensions. In turn, the agents have been able to represent the intentions associated with each style of behavior and to take advantage of their style of behavior just as face-to-face meetings take advantage from the heterogeneity of their participants.

The rest of the paper is organized in the following order: in the next section, we present several models (under the topic of psychology) that can be used by computer science scientists to model computer agents with human' characteristics/features. In Section 3, we expose the related work and in Section 4 we introduce the considered behavior styles and the dimensions in which they are defined. The study of operating values for behavior dimensions and their homogeneity is addressed in Section 5 and in Section 6 the agents are modelled with the proposed behavior styles and several experiments are performed. In Section 7 the discussion is presented. Finally, some conclusions are taken in Section 8, along with the work to be done hereafter.

2. Literature Review

In this section, we put forward some models that can be used by computer scientists to model agents with typically human characteristics. A current problem in the humanization of agents is related to the lack of knowledge there still is about human psychological functioning, and perhaps ever more so regarding the formalization of such knowledge. This problem often leaves computer scientists prone to devise strategies that would still benefit from stronger scientific validation. In this regard, a greater investment in multidisciplinary teams becomes of uppermost importance. Next, we advance some models that, in our view, show the potential of being adapted to computational systems, regardless of whether they are simulators or real systems.

Kilmann and Thomas (1975), based on Jung's studies and a conflict-handling mode proposed by Blake and Mouton (1964), suggested a model for interpersonal conflict-handling behavior, defining five modes: competing, collaborating, compromising, avoiding and accommodating, according to two dimensions: assertiveness and cooperativeness.

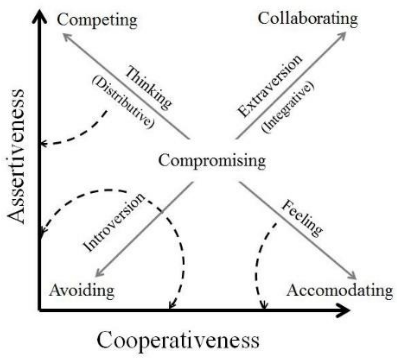

Figure 1. Thomas and Kilmann's model for interpersonal conflict-handling behavior, adapted from (Kilmann & Thomas, 1975)

As seen in Figure 1, both the dimensions of assertiveness and cooperativeness are related to the integrative and distributive dimensions as discussed by Walton and McKersie (1965). Integrative dimensions refer to the overall satisfaction of the group involved in the discussion while the distributive dimension refers to the individual's satisfaction within the group. It is possible to see that the thinking-feeling dimension maps onto the distributive dimension while the introversion-extraversion dimension maps onto the integrative dimension. This association becomes more evident if we conceive competitors as the ones who seek the highest individual satisfaction and collaborators as the ones who prefer the highest satisfaction of the entire group. On the other hand, avoiders, do not worry about group satisfaction and accommodators do not worry about individual satisfaction. They also concluded that the thinking-feeling dimension did not move towards the integrative dimension, and that the introversion-extraversion did not overlap with the distributive dimension.

McCrae and John (1992) proposed a set of thirty traits extending the five-factor model of personality (OCEAN model). Based on the most commonly accepted Big Five "buckets of traits", Costa and McCrae (1992) presented a model that comprises the dimensions of: (a) Negative Emotionality: as an individual's susceptibility to negative emotions and a general discontent with life; (b) Extraversion: broadly taken as the number of relationships with which one is comfortable; (c) Openness: referring to the number of interests, i.e., the variety and depth of information one is to prone to explore; (d) Agreeableness: measured by the one's willingness to takes norms for behavior while deferring to figures of authority; and (e) Conscientiousness:

resulting from the number of goals on which one is focused, where an high consciousness level means to be able to focus on a limited number of goals and to exhibit a high self-discipline. The traits then included six facets for each of the factors described above. These traits were used in a study made by Howard and Howard (1995) in order to help them separate different kinds of behavior styles and identify corresponding themes. A theme is defined as "a trait which is attributable to the combined effect of two or more separate traits". Those styles and themes are based on common sense and general research, and can be inferred such as the conflict styles that were proposed, (Negotiator, Aggressor, Submissive and Avoider), however it is also important to refer other relevant styles that were suggested such as the Decision and Learning styles. Decision style includes the Autocratic, Bureaucratic, Diplomat and Consensus themes while Learning style includes the Classroom, Tutorial, Correspondence and Independent themes.

Rahim (1983) created a meta-model of possible styles for handling interpersonal conflict based on two dimensions: Concern for self and Concern for the other. Later, Rahim and Magner (1995) performed a study to assess the construct validity of the five subscales of the Rahim Organizational Conflict Inventory (Rahim, 1983). The styles defined by Rahim (1983) are presented in Figure 2 and have been adapted to our problem. Rahim (1983) acknowledge the existence of 5 types of conflict styles: Integrating, Obliging, Dominating, Avoiding and Compromising. In this work, they suggested these styles as means to describe different possible ways of behaving in conflict situations. Their proposed styles are defined according to the level of concern an individual shows for achieving one's own goal or follow other people's objectives.

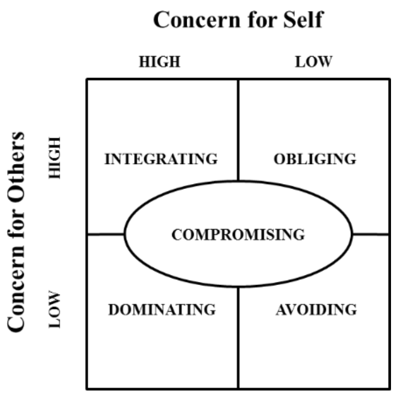

Figure 2. Conflict Styles, adapted from (Rahim & Magner, 1995)

The model proposed by Rahim (1983) also relates to the themes identified by Howard and Howard (1995) to a certain extent. The Aggressor theme resembles the Dominating style; the Negotiator theme resembles the Integrating style; the Avoiding theme resembles the Avoider style; and the Submissive theme resembles the Obliging style. The main difference is the existence of the Compromising style in the model proposed by Rahim (1983) which does not relate to a specific theme. In theory, the Compromising style is an intermediate state between the other styles that were identified. It is worth noting that in psychological literature, depending on its scope, it is often not consensual even the mere definition of single behavior styles. For example, what we conceive as "avoidance" for the sake of the present study may not reflect the subtleties of the concept as proposed elsewhere. For instance, when it is presented as an attachment style and therefore rendered as multifold. We would then have to consider avoiders that do not care and also the anxious, preoccupied avoiders that do care but won't engage, for regarding their actions as not useful or even as detrimental to the task in hand (Fraley & Shaver, 2000). Certainly, these examples and possible ramifications abound for all other behavior styles. Nonetheless we commit to Rahim's formulation as a basis for our work because, more than any other model, it has been largely grounded in organizational contexts, from which a great deal of his data has sprout. This too is our target of application.

3. Related Work

In this section, we present some works in the field of computer science, which somehow deal with cognitive and/or affective aspects. We began by taking a more general approach and later focus on work in the area of decision support or recommendation systems.

To rephrase Doyle, Cummins, and Pollock (1991), AI is the discipline aimed at understanding intelligent beings by constructing intelligent systems. In 1998, Castelfranchi (1998) said “AI is the science of possible forms of intelligence, both individual and collective”. In order to build intelligent systems, it is therefore absolutely necessary to first know the human being (its functioning) in order to later be able to use this knowledge in the development of systems. Multi-agent systems have been widely used in the last decades (Cao, Yu, Ren, & Chen, 2013; Jennings, Sycara, & Wooldridge, 1998). The level of autonomy associated with agents, their abilities to interact/communicate, as well as their capability to exhibit “behaviors” are highly praised features in ever more distributed environments (Ito & Shintani, 1997; Jennings & Wooldridge, 1998; Van der Hoek & Wooldridge, 2008). Many approaches have been put forward in literature, where agents are defined with characteristics that set them apart from each other (Allbeck & Badler, 2002; Badler, Allbeck, Zhao, & Byun, 2002; Velsquez, 1997; Zamfirescu, 2003). Also under the topic of group decision-making several works with agents have been proposed (Aronson, Liang, & Turban, 2005; Olfati-Saber, Fax, & Murray, 2007), some of which used agents as a way to represent decision-makers/experts (Joao Carneiro et al., In Press, 2017; Iván Palomares & Martínez, 2014b; Santos et al., 2009b). This representation of decision-makers allows the systems to become more intelligent and dynamic, given they are capable of dealing with aspects of great relevance in face-to-face type meetings. Zamfirescu (2003) proposed a model with two kinds of agents: interface agents and resources agents. Interface agents support each member that takes part in the meeting, including the group facilitator. Resources agents provide services for the rest of the system (communication services, decision support system services, and information recovery services). Iván Palomares and Martínez (2014b) used agents to represent experts. To minimize the needed interactions with the system, the experts can model the agent that represents them according to 1 of 3 profiles: sure profile, unsure profile and neutral profile (see below for a more detailed description). Santos, Marreiros, Ramos, Neves, and Bulas-Cruz (2009a) used agents to represent decision-makers and used the Five Factor Model to model the agents with different personalities: Aggressor, Submissive, Negotiator and Avoiding.

To model agents with human-like’ aspects is not new. At the beginning of the new millennium, some projects related to the agents’ humanization began to appear (André et al., 2000; Ball & Breese, 2000; Franklin, Kelemen, & McCauley, 1998).

Becker, Kopp, and Wachsmuth (2004) presented system that takes into account the emotions and mood of a conversational agent. Like most works since then, they use the OCC model by Ortony, Clore, and Collins (1990) to deal with emotions. The emotions are represented in an “emotion axis” and the mood in an “orthogonal axis” that stands for an undirected, longer lasting system state. In addition, they ponder “boredom” in order to deal with the absence of stimulus that the agent may face. In this way, they get the agent to express their emotional state according to the content of the conversation. They presented an experience in which the agent leaves the scene when it begins to feel insulted.

André et al. (2000) presented a paper where they describe the functioning of three projects that integrate lifelike characters. They considered that the growth in the number of research projects related to humanization with the goal of make human-computer interaction more enjoyable had become noticeable. To make the psychological modeling of the agents they also used the OCC model (to model the emotions) (Ortony et al., 1990) and the Five Factor Model (FFM) (to model the personality) (McCrae & John, 1992). They stressed the importance of taking into account affective issues in user-agent interactions. However, they did not present any type of data that quantified how the models proposed by them allow to obtain more satisfactory utilization processes.

Gmytrasiewicz and Lisetti (2002) presented a research work where they included a formal definition of emotional states and personality in a typical rational agent design based on decision theory. This work is especially relevant due to the hypothesis put forward by the authors: “the main hypothesis of our work is that notions of personality and emotions are useful in designing competent artificial agents that are to operate within complex uncertain environments populated by other artificial and human agents”. The authors used the OCC model (Ortony et al., 1990) to define the emotional states of the agents. Thus, they correlated these emotional states with different modes of decision-making. This means that each emotional state is associated with a decision-making situation. They also consider the personality of the agent, but do not use any specific personality model. They consider the personality of the agents as a set of emotional states the agent is capable of being in. Basically, the agents can vary their personality according to the three emotional states considered by them: cooperative, slightly annoyed and angry. The transitions that can occur between these states happen due to environmental inputs that they divided into 2 categories: cooperative and uncooperative. Although they point to several advantages and possible uses of the proposal, one cannot really say that there is a true verification of the research hypothesis. This can be seen in their own word, in the conclusions “we believe, will significantly enhance the applications of intelligent systems ...”.

Lorini and Falcone (2005) presented work in which they deal with the expectations of pro-active agents. They point out that one of the most distinctive aspects of intelligent agents is that they are proactive, meaning that they have to be able to deal with the future and to represent that future or the possible future effects. For this, in this work they provide a precise characterization of anticipatory mental states, to analyze their role in the generation of Surprise, Relief and Disappointment. This allows the agents to have a clear comprehension of the surprise phenomenon. In addition, the proposed approach allows an $Agent_i$ that expects an $Agent_j$ to take an action that is negative for it, develops a negative strong expectation, causing it to persuade the $Agent_j$ to stop doing this action.

Nowadays, there are many proposals that intend to model human-beings’ aspects in agents, such as: personality (Dimuro et al., 2007; Padgham & Taylor, 1997), emotions (Ball & Breese, 2000; Gmytrasiewicz & Lisetti, 2002), cognitive styles (Frank et al., 2001), etc. There are also some few proposals under the topic of GDSS (Ivan Palomares et al., 2014; Iván Palomares et al., 2013; Recio-García et al., 2013; Santos et al., 2009b). All of them share the idea that the inclusion of cognitive/affective aspects may somehow help the decision-making process. However, (to the best of our knowledge) most of them are oriented to be used in simulated environments. The usage of such techniques in real systems can bring some disadvantages. “A real me” can be a bad approach if my persona is less persuasive/intelligent/capable than others. No one will be interested in using an application that harms oneself. We will now present some recent proposals under the topic of decision-making that include agents and other important technical issues.

Miranda, Abelha, Santos, Machado, and Neves (2008) presented a scientific work where they developed a simulated medical practice scenario for intelligent decision support in the area of staging of cancer. The decisions were taken in the context of a group meeting in order to facilitate the collaborative work. They used agents that could exchange and store information to mirror real participants. The system emulated the TNM (Classification of Malignant Tumors) cancer staging system, increasing performance and eliminating paper circulation.

Santos et al. (2009b) presented a scientific work where they proposed a multi-agent architecture model designed to support groups in the decision-making process. The novelty of their work is the possibility to model the agent's personality. The idea is to humanize agents and with that, facilitate the negotiation process. They used four personality types (Negotiator, Aggressor, Submissive and Avoider) based on the Five Factor Model (McCrae & John, 1992) to define the agents' personalities. To select the agent's personality, each decision-maker needs to answer a questionnaire named Big Five Inventory (John, Donahue, & Kentle, 1991). They also proposed a simple negotiation model where the agents use the personalities to choose which kind of requests they should send and to process the received requests. The publication does not include any case study; however, the content is very interesting because the proposed model is based in strong assumptions existent in the literature.

Vallejo, Albusac, Castro-Schez, Glez-Morcillo, and Jiménez (2011) proposed a multi-agent architecture for supporting distributed intelligent surveillance based on a scalable normality analysis model. This scalable formal model, allows to define and identify the normality of an environment based in different issues (object speed, proximity relationships, etc). The proposed architecture is composed by three levels: reactive level, deliberative level and user level. The researchers implemented a prototype based on the proposed architecture to monitor a real urban traffic environment. The objective was to analyze the trajectories and speed of moving objects. They concluded that the use of normality analysis improves the flexibility of the proposed approach. In addition, they claimed that future systems based on this architecture can be easily extended when it is needed. They also stated that the proposed architecture meets some important surveillance requirements, such as scalability and robustness. Finally, the prototype was proven to work well when the number of situations is higher and the environments are tougher.

Iván Palomares et al. (2013) presented a Web-based consensus support system that permits the integration of the decision-makers' attitude regarding consensus. They study the importance that decision-makers place in reaching consensus regarding the possibility of modifying their own preferences. Decision-makers can/adopt three attitudes: pessimistic, indifferent and optimistic. For example, a decision-maker who adopts an optimistic attitude, means that for him to reach the agreement is more important than his own preferences. In this way, the group's options will be given more importance. They argue that (as might be expected) optimistic attitudes help to reach consensus while pessimistic attitudes hamper the achievement of consensus.

Recio-García et al. (2013) presented a group decision support system where each decision-maker is represented by an agent who argues with the other agents in order to achieve the best alternative for the group. The presented negotiation model includes the users' social factors, personality and trust in the argumentative process. The personality of decision-makers is represented by a number ranging from [0,1] where 0 means a very cooperative person and the reflection of a very selfish one. To study the trust, they use the interaction of decision-makers in social networks through a set of 10 factors. For the argumentation model, they used D^{2}ISCO, which is a platform for the design and implementation of deliberative and collaborative CBR applications. They concluded that the proposed model allows to achieve better satisfaction rates when compared to the standard "fully connected" group recommender.

Abraham, Flager, Macedo, Gerber, and Lepech (2014) performed a study on the impact of using a Multi-attribute decision-making (MADM) techniques and data visualization methods in group decision-making processes as a way to help reaching consensus. The authors refer that despite the benefits of using this type of techniques being generally recognized, their true impact had never been previously discussed. In this study they perfomed four charrettes, in each of them participants were divided in teams ranging from 3-5 elements and the teams were divided into 4 groups. The 1st group had no access to MADM techniques nor to visualization methods, the 2nd group had access to MADM techniques but had no access to visualization methods, the 3rd group had no access to MADM techniques but had access to visualization methods and the 4th group had access to both. They concluded that the use of MADM methods helps the group to reach consensus, but more important they managed to understand that the use of visualization techniques helps decision-makers to show the clients the reasons for which a certain proposal is made.

Iván Palomares and Martínez (2014b) presented a semisupervised consensus support system (CSS) based on the multiagent system paradigm. The main purposes are to overcome the difficulties associated with managing large groups of experts and the need for constant human supervision. In order to minimize the need for experts' interactions with the system, they defined a strategy that allows the experts to express their individual concerns. To do so, they defined three different profiles: sure profile, unsure profile and neutral profile. The first, intends to represent experts that are very confident about their preferences. Therefore, they do not intend to change them. The second, represents experts that want to achieve a consensus but are unsure about their opinions. The third, represent the experts that want to achieve a consensus and are moderately sure about their opinions. They conducted a case study made up by a set of experiments with the intent of understanding the different evolution of the degree of consensus between the proposed semisupervised CSS and a full-supervised CSS. They concluded that through the proposed system it was possible to minimize the need for expert human supervision and more importantly, they concluded that their proposal helps to achieve high levels of consensus faster than the full-supervised CSS.

Iván Palomares and Martínez (2014a) published a very interesting work about a tool that aims to help the decision-makers to reach consensual decisions in urgent situations. To do so, they put forward a visual decision support tool that can represent the experts' preferences. This tool is based on Self-Organizing Maps and consists in a two-dimensional visual representation that allows to perceive the existing levels of agreement/disagreement. The preferences are visually represented based on their similarities. They developed an experiment to demonstrate the usefulness of the proposed tool, succeeding to demonstrate that the proposed tool may help decision-makers reach consensus more easily, as well as to have a better perception of the current status of the decision process.

4. Styles of behavior in the context of group decision-making

In order for decision-makers to choose a style of behavior that mirrors their intentions (to model the agent that represents them), first and foremost it is necessary to define the mode of action of each of the styles considered. The approach proposed in this work was based on the model proposed by Rahim (1983) and subsequently studied more thoroughly in Rahim and Magner (1995), for being the one we consider to be the most appropriate for the context of this work. As we saw earlier (Section 2), Rahim (1983) proposed 5 styles of handling interpersonal conflict (Dominating, Integrating, Compromising, Obliging and Avoiding). He differentiated the styles of handling interpersonal conflict along two basic dimensions: Concern for self and Concern for others. The Concern for self explains the degree (high or low) to which a person attempts to satisfy his or her own concerns. The Concern for others explains the degree (high or low) to which a person wants to satisfy the concerns of others (Rahim & Magner, 1995). These dimensions were considered to represent the motivational orientations of a given individual during conflict (Rahim & Magner, 1995).

In this work, as a first step, we take on the conflict styles proposed by Rahim (1983) and we call them behavior styles. The designation of behavior styles is preferred for expressing something more comprehensive that serves for example to define the activity level of the agent. In addition, the idea is that a decision-maker can select a behavior style for the agent that represents him/her in a context of group decision-making. This behavior may vary throughout the process, i.e., the decision-maker must be able to change the behavior of the agent whenever he/she sees fit. Also, we define each behavior style specifically for the context of group decision-making:

- **Dominating**: An individual functioning according to a Dominating style feels that he/she holds the key to the problem. The individual actively engages in the decision-making process and seeks to impose his opinion on others;
- **Obliging**: An Obliging functioning easily tends to yield his position to follow the interests of the group, choosing to follow the opinions of others instead of sharing his own;
- **Avoiding**: An Avoiding functioning is related to disengagement. Such an individual seeks not to be involved in decision-making, devaluing both the process and the opinion of all stakeholders;
- **Compromising**: A Compromising functioning privileges a collaborative style. It seeks to reach consensual decisions, valuing both their own opinions and those of others in the group. Here, the individual is moderately involved in the decision-making process;
- **Integrating**: An Integrating functioning privileges a collaborative style. It seeks to achieve consensual decisions, valuing both their own opinions and those of others very much. The individual prefers to manage the entire decision process in a highly committed manner.

As we mentioned earlier, Rahim (1983) used two dimensions (Concern for self and Concern for others) to differentiate conflict styles. Each style was rated in these dimensions according to 2 levels (Low or Mid). Later, in Rahim and Magner (1995), "there are 3 levels", since they consider "Compromising" as a style that "involves moderate concern for self as well as the other party involved in conflict".

In this work, we also consider the two dimensions proposed by Rahim (1983) to define agent behavior due to its high relevance in the context of group decision-making. However, to properly define the mode of action of each of the behavior styles in this context, these 2 dimensions are not sufficient. For this, we correlated the conflict styles proposed by Rahim (1983) with conflict styles proposed by Howard and Howard (1995) (see Table 1).

Table 1. Proposed correspondence between Rahim's and Howard and Howard's conflict styles

Rahim (1983)	Howard and Howard (1995)
Dominating	Aggressor
Integrating	Negotiator
Compromising	-
Obliging	Submissive
Avoiding	Avoider

The conflict styles proposed by Howard and Howard (1995) are defined using 4 of the 5 factors of the Five Factor Model (McCrae & Costa, 1995). The factors used are: Negative Emotionality (N), Extraversion (E), Agreeableness (A) and Conscientiousness (C). Table 2 presents the classification of the conflict styles proposed by Howard and Howard (1995). A plus sign (+) indicates a score above 55; a minus sign (-) indicates a score below 45, and a letter with no plus or minus indicates a score in the 45-55 range. The 45-55 range comprises one standard deviation in the middle/from the mean of the population.

Table 2. Conflict styles proposed by Howard and Howard (1995)

Theme	Components
Negotiator	N, E(+), A, C(-)
Aggressor	N+, E+, A-, C+
Submissive	N-, E-, A+, C-
Avoider	N+, E-, C-

Because Howard and Howard's conflict styles are classified in this way, it becomes possible to perceive/describe them through the facets that Costa and McCrae (1992) defined for each factor. Table 3 presents a small example of some of the facets related to the "Extraversion" factor. We can see that the conflict style "Aggressor" (see Table 2) can be described as: "prefers company", "a leader" and vigorous. On the other hand, the "Submissive" can be described as: "prefers alone", "in background" and "leisurely".

Table 3. Example of some of the facets related to the "Extraversion" factor

Extraversion	Introvert (E-)	Ambivert (E)	Extravert (E+)
Gregariousness	Prefers alone	Alone / others	Prefers company
Assertiveness	In background	In foreground	A leader
Activity	Leisurely	Average pace	Vigorous
…	…	…	…

We use the facets proposed by Costa and McCrae (1992) to identify the remaining dimensions necessary to define our behavioral styles. The first dimension is that of "Resistance to change" which is related to the facets identified in the "Agreeableness" factor. The second dimension is that of "Activity Level" which has to do with the facets identified as the "Extraversion" factor. With our dimensions already identified we are now in position to describe them in this context of group decision-making.

- **Concern for self**: This dimension is concerned with how much the decision-maker values achieving his or her own goals. It directly influences the number of requests that will be made by the agent. An agent with a higher concern for self makes more requests to achieve his/her goals faster;
- **Concern for others**: This dimension is related to the extent to which the decision-maker values achieving the objectives of the group, or of a subgroup of decision-makers that he considers important/credible. An agent with a high degree of concern for others has a wider ability to accept certain types of requests;
- **Resistance to change**: This dimension is related to the ease with which the agent accepts requests. This means that an agent with a high resistance to change is much less able to accept requests than an agent with a low resistance to change;
- **Activity level**: This dimension is related to the level of participation of the agent in the process. An agent with a high level of activity level engages more in the process, carrying out more questions and affirmations/statements. On the other hand, an agent with a low activity level is less interventive, limiting himself to responding rather than starting new dialogue topics.

We present in Table 4 the classification of each of our behavioral styles in each of the dimensions identified. This classification is completely theoretical, based on the data found in the literature.

Table 4. Classification of behavioral styles in the considered dimensions (Low, Mid, High)

Styles of behavior	Concern for self	Concern for others	Resistance to change	Activity level
Dominating	High	Low	High	High
Integrating	High	High	Mid	Mid/High
Obliging	Low	High	Low	Low
Compromising	Mid	Mid	Mid	Mid
Avoiding	Low	Low	Low	Low

Seen that there is no conflict style in Howard and Howard (1995) equivalent to the "Compromising" conflict style in Rahim (1983), we assume that this behavior style in the dimensions of "Resistance to change" and "Activity Level" has a Moderate level. It is important to note that in this work and contrary to what happens in other works (Howard & Howard, 1995; Kilmann & Thomas, 1975; Rahim, 1983), we are not evaluating individuals themselves. We are grounding our study in already existing models to define behaviors in agents that represent people. This means that the important thing is for people to be able to understand a certain style of behavior in the same way when the style is to be selected. This means that if the population homogeneously considered the "Dominating" as having a low "Activity Level" low, it would not be problematic, as long as this understanding was identical.

5. Study 1

In this section, we intend to determine the operating values that can later be used to model our agents according to four dimensions: Concern for self, Concern for others, Resistance to change and Activity level. Based on these dimensions, we will be able to configure five behavior styles: Dominating, Integrating, Obliging, Compromising and Avoiding. In order to achieve this, first, as previously put forward in (h1) we needed to empirically validate the values that would correspond to each style of functioning. So, the step that follows implies asking a group of participants how do they perceive what is expected in terms of the behavior that each style would present in the context of group decision-making.

5.1. Method

5.1.1. Participants

In this study participants were 64 adults, 39 men and 25 women, aged between 19 and 68 years old (*M=33,56; SD=10,84*) all of which either had higher education degrees or were undergraduate students (10%). In respect to their fields of expertise, respondents were professionals from a wide variety of backgrounds, ranging from technology to social sciences. In Figure 3 we present their distribution.

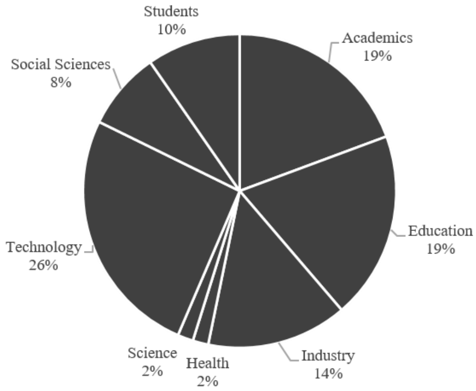

Figure 3. Distribution of participants according to area of expertise

5.1.2. Procedure

In this study, participants were asked to classify the five proposed behavior styles in four dimensions: (a) Concern for self; (b) Concern for others; (c) Resistance to change; (d) and Activity level in a questionnaire ranging from 0-10 (by means of a visual analogic scale). All respondents were asked to fill out the questionnaire in the researcher's presence to ensure engagement in the task and/or to provide assistance in the clarification of concepts or modes of signaling the answers.

To define "Concern for self", participants were asked "how worried about achieving his/her own objectives" is each style of functioning; to define "Concern for others" they were asked "how worried about achieving other's objectives" do they consider each behavioral style to be; to measure "Resistance to change" participants were asked "how likely to resist change" do you think each behavioral style is; and to measure "Activity level" participants were asked "how interventive" do they consider each behavioral style to be.

To make it apprehensible, an example-situation was presented to the participants, concerning a hypothetical planning of a dinner (choosing a restaurant) in the context of a group.

Actual instructions read as follows:

The present study intends to contribute to the development of a tool that allows to assist several professionals in group decision-making processes. Each person will be represented by a virtual decision-maker – a "robot" – that acts according to a type of behavior he chose. You may think of him as if he was your "virtual assistant". This way you may choose your behavior style among multiple profiles and then delegate to him the function of making decisions on your behalf, in interaction with other agents either real or virtual.

For a better understanding, note the following example:

> "*Imagine that you worked in an organization and that your team would have to take part in choosing the restaurant where the Christmas dinner would be held. Certainly, there would be several possible options and also several criteria that would guide the discussion of the group, such as: the distance to the restaurant, the average price of the meal, the waiting time, the existence or not of a smoking area or even the desire to please the tastes of the team leader. Whatever the priorities might be, your assistant could represent you according to higher or a lower interest in forcing your position or let yourself be led by the opinions of others. Here are 5 types of functioning you could set for your assistant.*"

After collecting the data from the 64 respondents, we could have values for mean and standard deviation for all four dimensions, which allowed us to compare each one according to all five behavior styles and also have numeric values for later use (in Study 2). Here, we present mean values and standard deviations for Concern for self (Figure 4), Concern for others (Figure 5), Resistance to change (Figure 6) and Activity Level (Figure 7).

5.2. Results

In this sub-section, we will report the values we obtained from our group of participants, that later will be used to model agents with the five behavior styles that we proposed. Values for each style will be grouped according to the four behavior dimensions that were evaluated.

Regarding the dimension Concern for self, the clearly highest scoring styles of behavior are Dominating (*M=9,47; SD=0,54*) and Integrating (*M=7,77; SD=1,43*), in this order. It is worth noting that when defining the values of Concern for self, participants showed more variability for the Integrating style. Then we have "medium" values for Compromising (*M=5,48; SD=0,67*) and "low" and "very low" for Obliging (*M=1,97; SD=1,19*) and Avoiding (*M=1,08; SD=0,93*), respectively. We may be in the presence of a bottom effect regarding this dimension and style of behavior. In Figure 4 we present the box plot of each style of behavior regarding the dimension Concern for self.

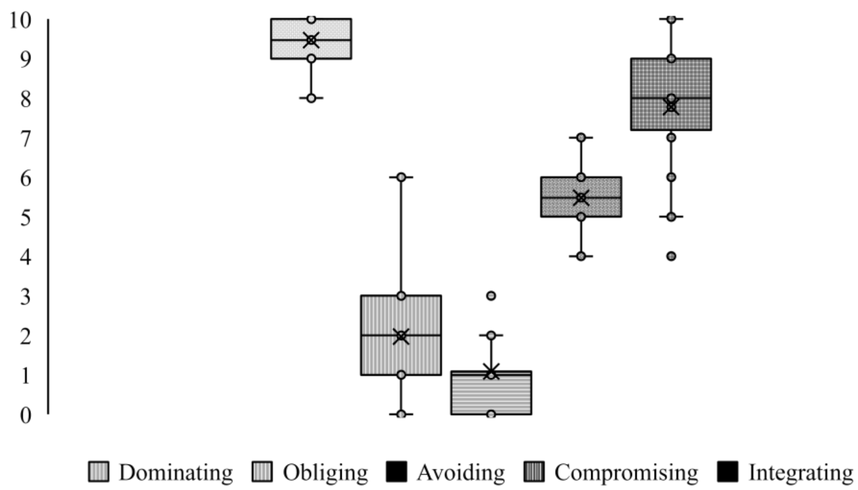

Figure 4. Box plot of concern for self

Regarding the Concern for others dimension, there are clearly three high scoring styles of behavior, in a decreasing order: Obliging (*M=8,73; SD=0,97*), Integrating (*M=8,46; SD=0,81*) and Compromising (*M=6,16; SD=1,33*) and two (very) low scoring styles: Dominating (*M=1,71; SD=1,44*) and Avoiding (*M=0,90; SD=0,91*). In Figure 5 we present the box plot of each style of behavior regarding the Concern for others dimension.

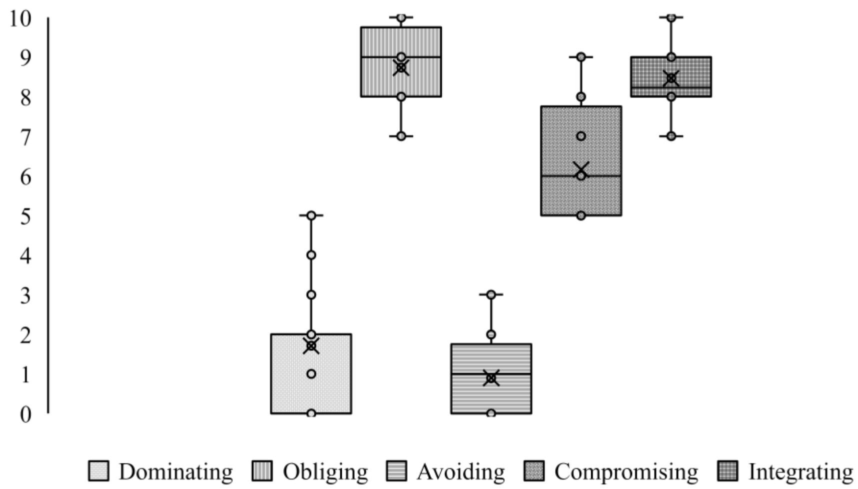

Figure 5. Box plot of concern for others

In the Resistance to change dimension, the Dominating style clearly stands out as the highest scoring style (*M=9,16; SD=0,71*). Then, in a decreasing manner, Integrating (*M=5,43; SD=0,49*) and Compromising (*M=4,16; SD=1,23*) score "medium" values, and Obliging (*M=1,24; SD=0,82*) and Avoiding (*M=0,96; SD=0,88*) present "low" values. In Figure 6 we present the box plot of each style of behavior regarding the Resistance to change dimension.

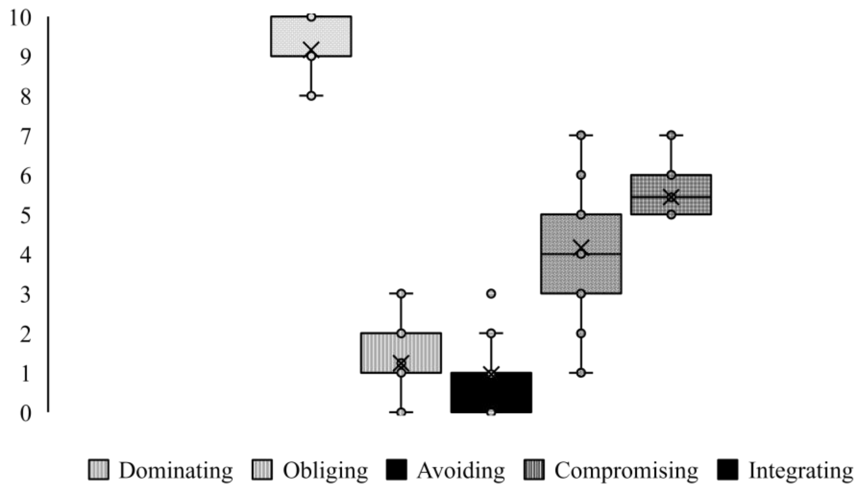

Figure 6. Box plot of resistance to change

The highest values found for the dimension of Activity level are those of the Dominating (*M=9,38; SD=0,63*) and Integrating (*M=9,00; SD=0,87*) styles. Compromising (*M=5,84; SD=1,30*) has a "medium" value and both Obliging (*M=2,28; SD=1,28*) and Avoiding (*M=0,52; SD=0,59*) styles present a "low" activity level. In Figure 7 we present the box plot of each style of behavior regarding the Activity level dimension.

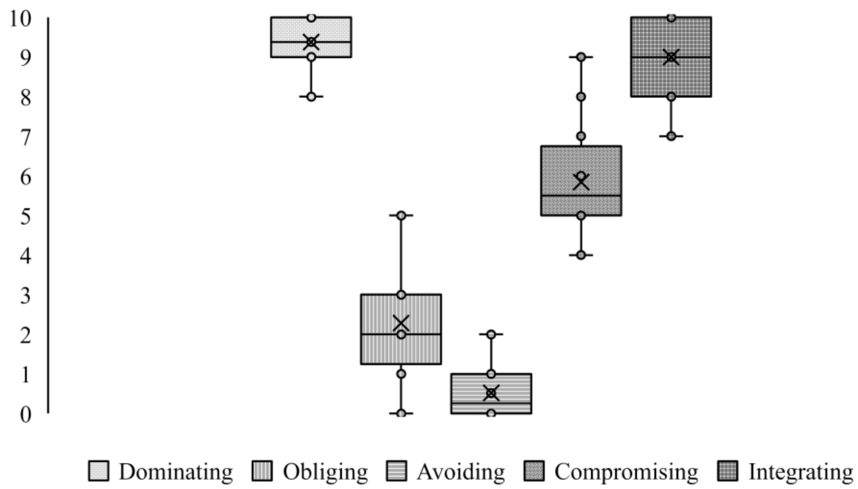

Figure 7. Box plot of activity level

With the purpose of assessing the consistency/reproducibility of the measurements made by our participants, next we present Intraclass Correlation Coefficient (ICC) for each of the behavior dimensions studied. For all dimensions results are above *,900*, more precisely between *,915* and *,941* so the agreement level can be considered excellent by any standards, for example Cicchetti (1994). We also can see that in all dimensions, results are highly significant (*p<,001*). In sum, these results show that our participants highly agree on how to define the dimensions of Concern for self, Concern for others, Resistance to change and Activity level both in magnitude in relative position across the five behavior styles. The same is to say that there is very high agreement on how to attribute different values according to the behavioral styles and also on how the 5 of them should be ordered within each of the 4 dimensions, which certainly may prove useful when presenting options for a problem/agent configuration. Table 5 presents ICC values for each dimension, with the responses of 64 participants for 5 behavior styles.

Table 5. ICC values for each dimension

Intraclass Correlation Coefficient – Concern for Self							
	Intraclass Correlation[b]	95% Confidence		F Test with True Value 0			
		Lower Bound	Upper Bound	Value	df1	df2	Sig
Single Measures	,927[a]	,818	,991	797,442	4	252	,000
Average Measures	,999[c]	,997	1,000	797,442	4	252	,000
Intraclass Correlation Coefficient – Concern for Others							
	Intraclass Correlation[b]	95% Confidence		F Test with True Value 0			
		Lower Bound	Upper Bound	Value	df1	df2	Sig
Single Measures	,915[a]	,791	,989	744,848	4	252	,000
Average Measures	,999[c]	,996	1,000	744,848	4	252	,000
Intraclass Correlation Coefficient – Resistance to change							
	Intraclass Correlation[b]	95% Confidence		F Test with True Value 0			
		Lower Bound	Upper Bound	Value	df1	df2	Sig
Single Measures	,938[a]	,842	,992	1017,069	4	252	,000
Average Measures	,999[c]	,997	1,000	1017,069	4	252	,000
Intraclass Correlation Coefficient – Activity Level							
	Intraclass Correlation[b]	95% Confidence		F Test with True Value 0			
		Lower Bound	Upper Bound	Value	df1	df2	Sig
Single Measures	,941[a]	,849	,992	1026,275	4	252	,000
Average Measures	,999[c]	,997	1,000	1026,275	4	252	,000

Two-way mixed effects model where people effects are random and measures effects are fixed.
a. The estimator is the same, whether the interaction effect is present or not.
b. Type A intraclass correlation coefficients using an absolute agreement definition.
c. This estimate is computed assuming the interaction effect is absent, because it is not estimable otherwise.

After what we presented for mean, standard deviation and ICC values, we are in position to state that we can safely rely on the attained values for their usage as operating values for the different styles of behavior. This way, we present in Table 6 average operating values for the 5 behavior styles so that they can be used in Study 2 as well as in future work that may rely on these variables.

Table 6. Mean values of each behavior style in the four dimensions

Behavior Style	Concern for self	Concern for others	Resistance to change	Activity level
Dominating	9,47	1,71	9,16	9,37
Obliging	1,97	8,73	1,24	2,28
Avoiding	1,08	0,9	0,96	0,52
Compromising	5,48	6,16	4,16	5,84
Integrating	7,77	8,46	5,43	9

6. Study 2

In this section, after having presented the attained operating values, we will assess whether computer agents can act according to the defined styles of behavior and if a group decision support system that uses agents modelled with behavior styles may benefit from their heterogeneity.

As we will see in Sub-Section 6.2, to run our experiments we implemented the argumentation-based negotiation model proposed in Joao Carneiro et al. (In Press, 2017), with a communication environment as proposed in Carneiro, Martinho, Marreiros, and Novais (2016b). However, for agents to have a social behavior equivalent to that performed by humans, it is necessary to define a correct communication flow. In a face-to-face meeting, decision-makers share the same space at the same time (DeSanctis & Gallupe, 1987). This means that when a decision-maker expresses himself/herself, whether it is verbal communication or otherwise, this communication is received by all other decision-makers at the same time. In a virtual environment, where agents communicate simultaneously, this reception is not done at the same time due to technological limitations. This situation means that at certain moments of time there are agents who are in possession of knowledge that other agents still do not have, and can benefit from that prior knowledge unintentionally. Therefore, in this work we propose a communication flow that guarantees impartiality, promoting a type of interaction similar to that realized by real decision-makers, in face-to-face type meetings.

6.1. Communication Flow

We assume that each decision-maker is represented in a GDSS by a participating agent (AgP). The participating agent seeks to represent the interests of the decision-maker. In addition, we also assume the existence of a facilitating agent (AgF). The AgF is responsible for managing the meeting, initiating/finalizing the process and managing/handling communications. In a simplistic way, the communication flow that we propose implements an acknowledgment mechanism that ensures the reception of the messages by the AgP before a new dialogue can be initiated.

In a first step the AgF notifies all AgP that the meeting started (Figure 8 – Step 1). Then all AgP notify the AgF that they are ready to start the meeting (Figure 8 – Step 2).

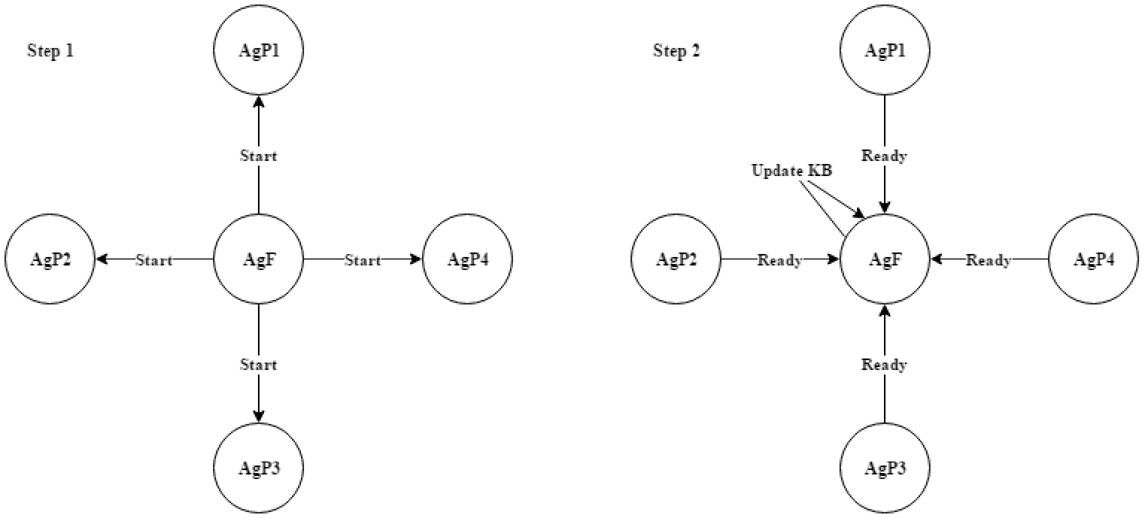

Figure 8. Communication Flow's Step 1 and Step 2

When the number of participating agents "Ready" equals the number of participants in the meeting process (see Figure 12), AgF invites AgP to start a new dialog topic (Figure 9 – Step 3). AgP generate a participation time based on their style of behavior (if they have something to say, otherwise they return "No") and send it to the AgF (Figure 9 – Step 4).

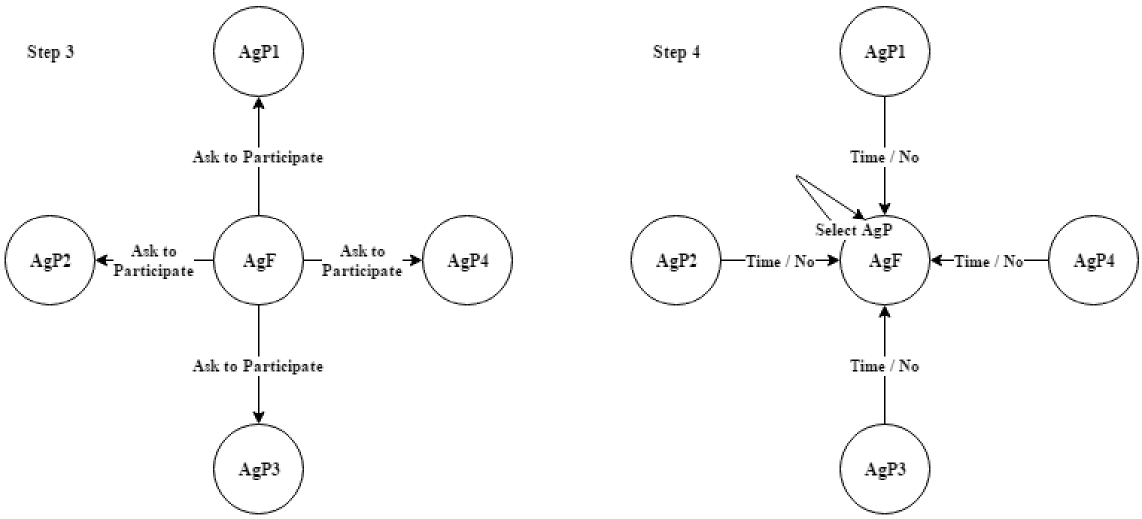

Figure 9. Communication Flow's Step 3 and Step 4

AgF (Figure 9 – Step 4) selects the AgP that sent a higher participation time (of course, participating agents with a higher activity level are more likely to be selected). Then the AgF notifies all AgP about the AgP that was selected (Figure 10 – Step 5). The selected AgP sends the message that it wants to transmit to AgF and AgF spreads this message to all other AgP (Figure 10 – Step 6).

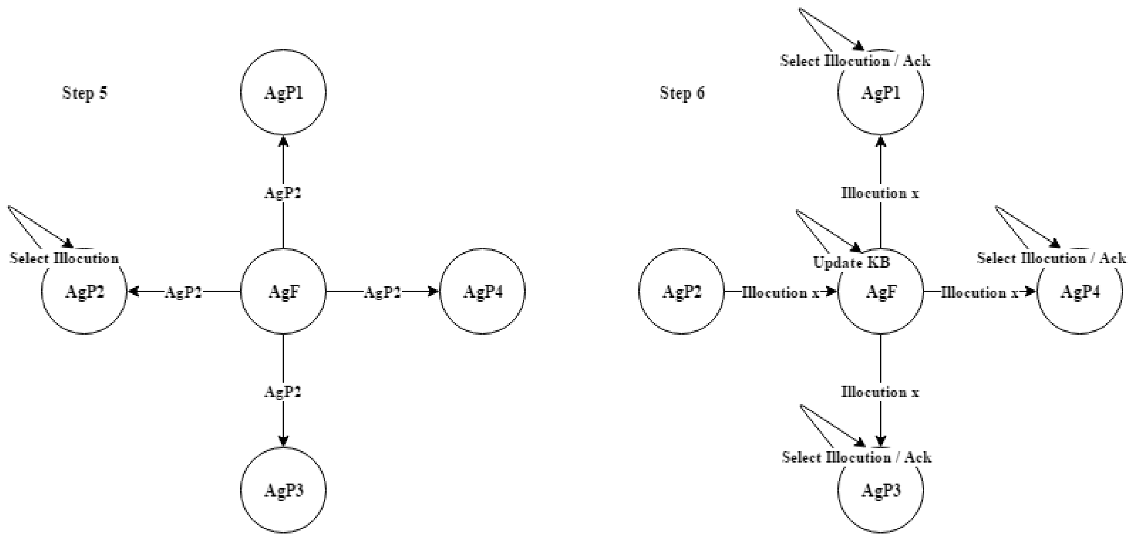

Figure 10. Communication Flow's Step 5 and Step 6

All agents who have received the message may respond with a new Illocution or if they have nothing to respond they send an acknowledgment to notify the AgF that they have received $Illocution_x$ (Figure 11 – Step 7). The first Illocution-type response that the AgF receives is sent to all AgP (repeating Step 6), causing all AgP that have responded to Step 7 with an Illocution to automatically know if the message being spread is theirs or not (Figure 11 – Step 8). For each Illocution that AgF diffuses through AgP it expects to receive $n-1$ responses (Illocutions or acknowledgments), where n is the number of AgP involved in the decision process. In the case of Figure 11 – Step 7, the AgF received 2 Illocution ($Illocution_y$ and $Illocution_z$) in response to $Illocution_x$. Therefore, AgF selects the Illocution it received first and sends this message to other AgP (Figure 11 – Step 8). AgP_3 who had previously attempted to make a communication ($Illocution_z$) may try to send his message again if it still makes sense given the new knowledge it has received ($Illocution_y$). When for each Illocution sent, there are $n-1$ responses, the process returns to Step 3.

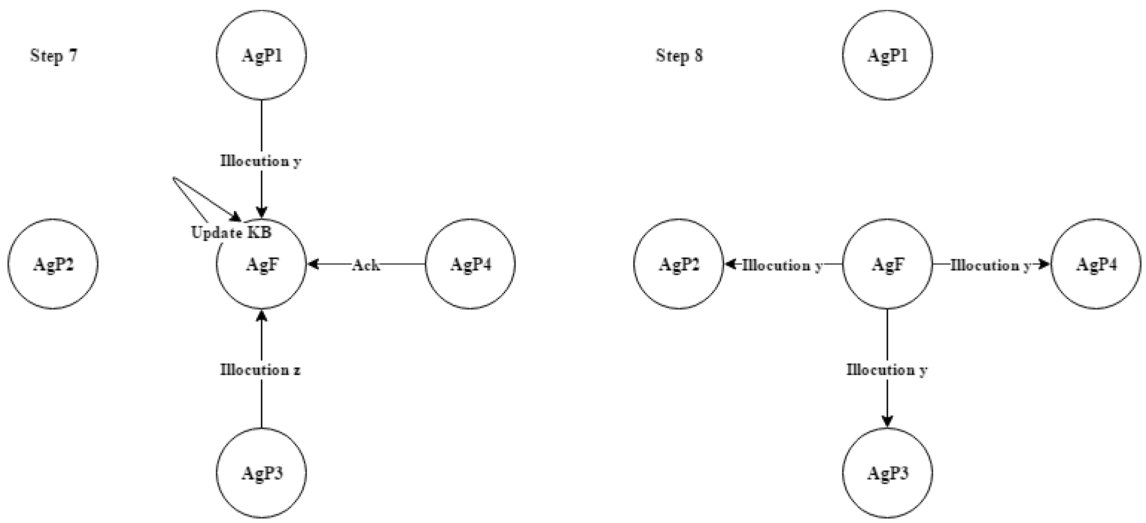

Figure 11. Communication Flow's Step 7 and Step 8

Now we will present the internal functioning of each of the agents involved in the process. As mentioned, the AgF is responsible for "managing" the meeting. In this way, it is responsible for initiating/finalizing the process and managing the flow of communication. Figure 12 shows the facilitator agent's flowchart. The AgF is responsible for initiating and terminating the decision process. Initially he starts by starting the meeting and expects all AgP to be ready. He then invites the AgP to initiate a dialogue and controls the flow of communication (as previously described). This process is repeated every time until one of two things happens: no participant agent wants to start a new dialogue or consensus has already been reached towards an alternative.

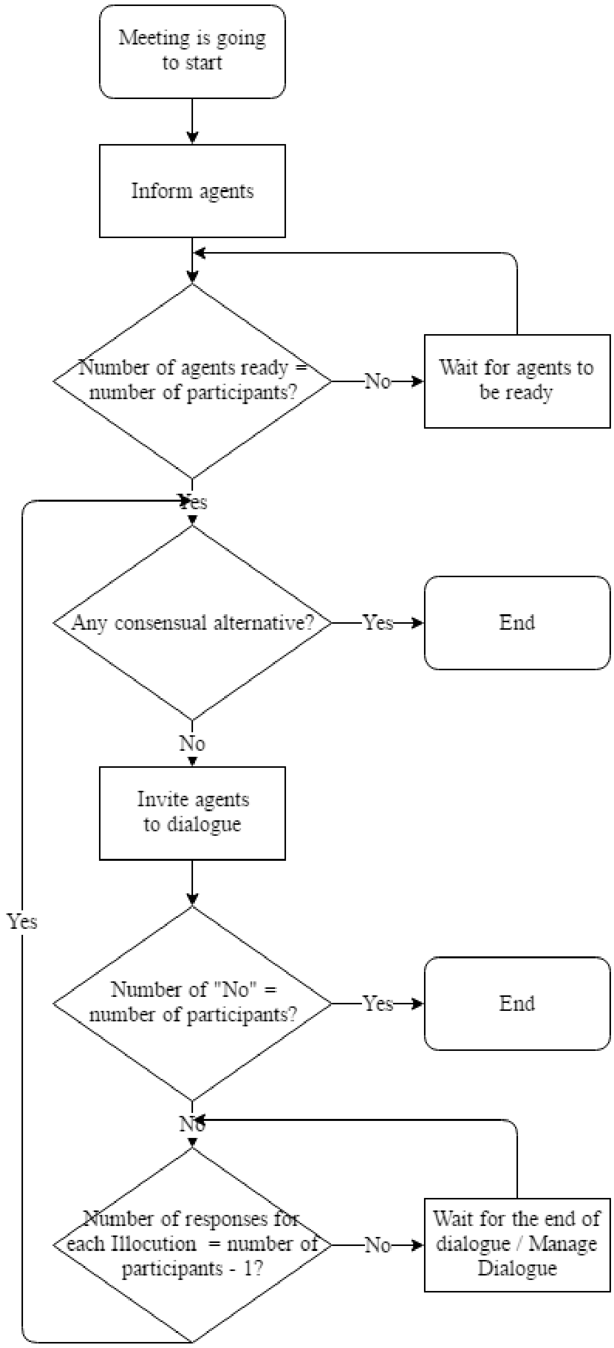

Figure 12. Facilitator agent's flowchart

Participating agents represent decision-makers in this virtual environment. In the communication environment proposed in Carneiro et al. (2016b) and on the basis of which we rely, participating agents can conduct two types of conversations: public conversations (as previously described) and private conversations of type 1 to 1, which are used only for making requests. When a participating agent is notified by the AgF that the meeting will is about to begin, the AgP will notify the AgF that it is Ready and sends back other information such as preferences and goals (Figure 13). After the meeting has all the conditions to begin, AgF invites AgP to start a dialogue, each AgP checks if it has something to communicate, if it does, it generates a participation number based on its style of behavior (Figure 13). If a certain AgP is selected to speak, it sends its message to the AgF otherwise it waits to receive a message (Figure 13).

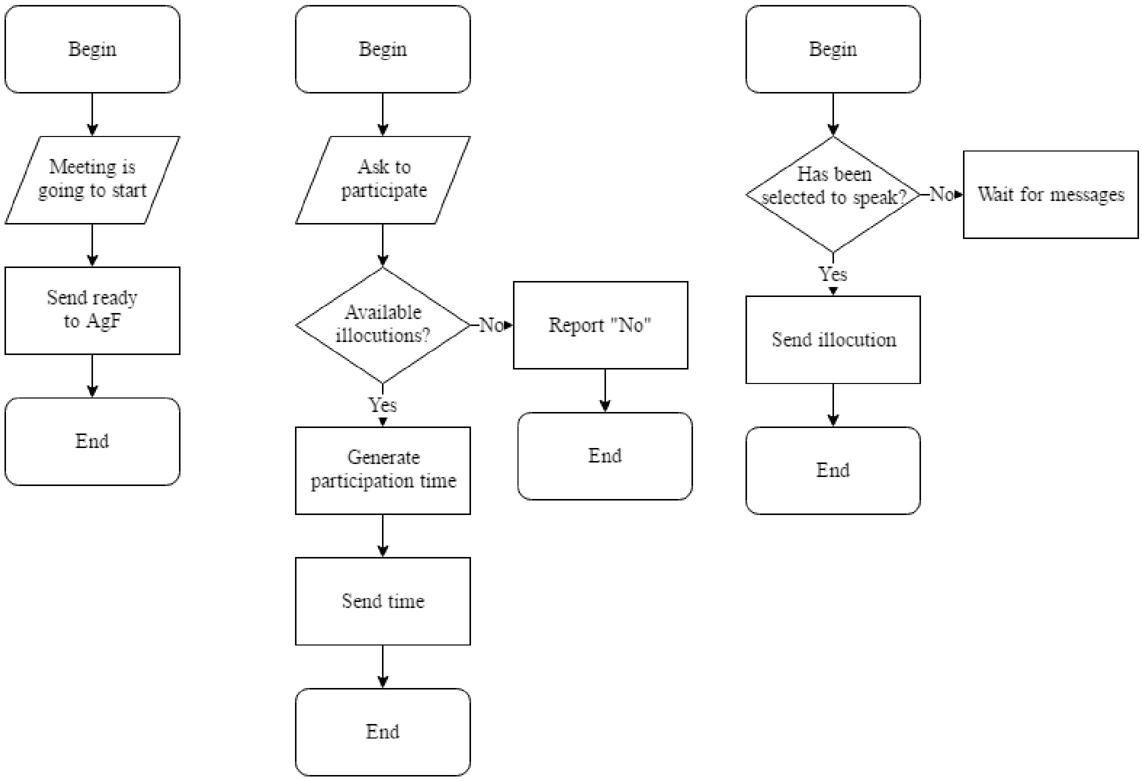

Figure 13. Participant agent's flowchart

Finally (Figure 14), when an AgP receives a new message it starts by checking which type of message, if it is a request (that is, it is a message from 1 to 1) it processes it and sends the response to AgP that had made the request. If it accepted the request, it will send a message to AgF to update it with his new preferences. If the message is not a request, it processes the message and checks if it has interest or conditions to respond to this message, if it does not send an "Ack" otherwise it sends a response. Each time an AgP receives a new message other than a request type message, it checks if this new information offers the conditions for it to make requests to other AgP, if this happens, it sends the requests (Figure 14).

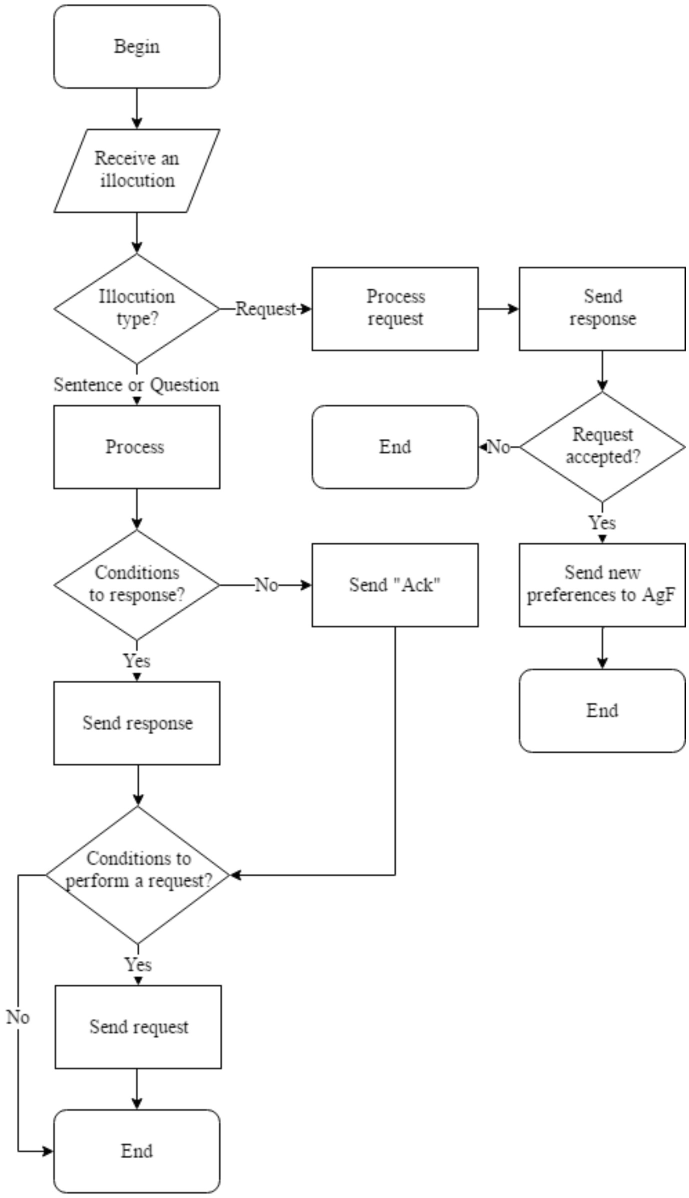

Figure 14. Participant agent's flowchart

6.2. Experiment

Communication flow was created with the objective of studying two very concrete hypotheses. The first one (h2) is to understand if the agents can correctly represent the decision-makers taking into account the data obtained in experiment 1. This way, we intend to study if using a face-to-face decision scenario, agents can actually display behavior according to the modelled values (in each of the dimensions proposed in study 1). The second hypothesis (h3) is related to perceiving what kind of "impact" each of the proposed behavioral styles has. As mentioned earlier, given that this proposal has as its main objective to be applied in systems that are used in the real world by real decision-makers, it would not make sense to have a style of behavior that would always be benefited. It would not make sense for decision-makers to know that, in the end, whoever chooses a particular style of behavior always wins. That would not represent the heterogeneity of the world we live in. The point about representing the intentions of decision-makers through behavioral styles is that they may serve as an advantage for all decision-makers because they would be better represented in the system.

To perform our simulations, we used a prototype (previously developed) that uses a negotiation architecture based on social networks (Carneiro et al., 2016b) and implements the argumentation-based negotiation model proposed in Joao Carneiro et al. (In Press, 2017).

To study (h2) we created 4 simulations environments, the first with 5 agents (1*Dominating, 1*Integrating, 1*Obliging, 1*Compromising, 1*Avoiding) the second with 10 agents (2*Integrating, 2*Obliging, 2* Compromising, 2*Avoiding), the third with 20 agents (4*Dominating, 4*Integrating, 4*Obliging, 4* Compromising, 4*Avoiding) and at last the forth with 40 agents (8*Dominating, 8*Integrating, 8*Obliging, 8* Compromising, 8*Avoiding). We have created several simulation environments because we considered at the outset that because agents act using different behavioral styles, their behavior may vary according to the number of agents and the behavioral style of the other agents with which they are involved in the decision process. We used the multicriteria problem previously used in case studies as presented in Carneiro, Martinho, Conceição, Marreiros, and Novais (2017); Carneiro, Martinho, Marreiros, and Novais (2016a) and each agent generated its preferences regarding the alternatives and criteria in a "random" way. Initially each agent randomly generated its preferences regarding the criteria and then, based on these preferences, it generated the preferences of the alternatives with a randomness that made would be plausible taking into account the values of the criteria of each alternative and preferences of previously generated criteria. For each simulation environment, we ran 100 simulations (100*4 in total).

Study of "Concern for self" dimension through the analysis of number of requests made by the agents

To study the dimension of "Concern for self" we have analyzed the number of requests made by the agents of each behavior style. Table 7 presents data related to the analysis of Concern for self. The μ[0,1] represents the values obtained in experiment 1 relative to the dimension of "Concern for self" in each behavior style. G. represents the values μ[0,1] normalized on a scale of [0,1], where the sum of all values equals 1. The μ represents the average number of requests made by each style of behavior over the 100 simulations. The σ represents the standard deviation of the number of requests made by each style of behavior over the 100 simulations. The Min. is the minimum number of requests made and the Max. is the maximum number of requests made in the 100 simulations. P. represents the values of μ normalized on a scale of [0,1], where the sum of all values is equal to 1.

Table 7. "Concern for self" dimension – number of requests made with n agents for the 5 behavior styles

			Dominating	Integrating	Obliging	Compromising	Avoiding
		μ[0,1]	0,95	0,78	0,20	0,55	0,11
		G.	0,36	0,30	0,07	0,21	0,04
Concern for self	5 Agents	μ	12,65	11,91	7,96	10,72	7,2
		σ	4,89	4,67	2,66	3,81	2,79
		Min.	4	2	3	3	2
		Max.	27	24	15	23	15
		P.	0,25	0,23	0,15	0,21	0,14
	10 Agents	μ	43,99	40,03	27,06	35,85	23,54
		σ	11,64	9,97	5,05	8,03	4,41
		Min.	22	19	13	21	10
		Max.	74	74	43	59	38
		P.	0,25	0,23	0,15	0,21	0,13
	20 Agents	μ	118,69	110,74	75,19	103,06	64,89
		σ	28,93	24,61	12,07	21,08	10,15
		Min.	55	56	42	53	40
		Max.	214	183	118	186	99
		P.	0,25	0,23	0,15	0,21	0,13
		μ	305,75	282,32	186,30	256,97	160,98

	σ	62,86	55,65	22,93	42,64	19,47
40 Agents	Min.	149	147	123	148	94
	Max.	499	540	268	381	227
	P.	0,25	0,23	0,15	0,21	0,13

We can verify that in all simulation environments and as expected, agents with the “Dominating” behavior style are the ones that make the most requests. On the other hand, the agents that perform the least requests are the “Avoiding” style ones. We also found that the values of G. and P. are slightly different. However, this is because although agents with behavior styles such as “Dominating” and “Integrating” are more likely to make requests, this probability is also affected by the argumentation system used. In this case, using the one proposed in Joao Carneiro et al. (In Press, 2017) they have a limited number of requests that can be made, which makes that in situations where agents do not quickly obtain consensus, these styles of behavior (“Dominating” and “Integrating “) no longer have requests to make, causing agents with other styles to approach the number of requests made by them.

In order to study the dimension “Concern for others” we analyzed the number of appeal to prevailing practice accepted by the agents of each style of behavior. The appeal to prevailing practice was used to study the “Concern for others” dimension because the only situation in which this dimension is used (according to the argumentation-based negotiation model implemented) is in the formula for evaluating this type of request. Table 8 presents data related to the analysis of “Concern for others”.

Table 8. “Concern for others” dimension – number of appeals to prevailing practice accepted by n agents for the 5 behavior styles

			Dominating	Integrating	Obliging	Compromising	Avoiding
		μ[0,1]	0,17	0,85	0,87	0,62	0,09
		G.	0,06	0,32	0,33	0,23	0,03
Concern for others	5 Agents	μ	0	0,09	0,16	0,11	0,19
		σ	0	0,28	0,36	0,31	0,39
		Min.	0	0	0	0	0
		Max.	0	1	1	1	1
		P.	0	0,16	0,29	0,20	0,34
	10 Agents	μ	0,015	0,11	0,17	0,09	0,11
		σ	0,12	0,31	0,41	0,30	0,31
		Min.	0	0	0	0	0
		Max.	1	1	2	2	1
		P.	0,03	0,22	0,34	0,18	0,22
	20 Agents	μ	0,01	0,08	0,18	0,09	0,07
		σ	0,11	0,28	0,42	0,30	0,26
		Min.	0	0	0	0	0
		Max.	1	2	2	2	1
		P.	0,02	0,18	0,40	0,21	0,17
	40 Agents	μ	0,008	0,09	0,17	0,06	0,06
		σ	0,09	0,30	0,39	0,25	0,27
		Min.	0	0	0	0	0
		Max.	1	2	2	2	2
		P.	0,02	0,23	0,41	0,16	0,16

The μ[0,1] represents the values obtained in study 1 relative to the dimension of “Concern for others” in each behavior style. G. represents the values μ[0,1], standardized on a scale of [0,1], where the sum of all values is equal to 1. μ represents the average number of common practices accepted by each behavior style over the course of the 100 simulations. The σ represents the standard deviation over the 100 simulations. The Min. is the minimum number of accepted requests and the Max. is the maximum number of requests accepted in the 100 simulations. P. represents the values µ of normalized on a scale of [0,1], where the sum of all values is equal to 1. In this case, we have verified that agents with the "Dominating" behavior style are the ones that accept fewer "common practices" requests. On the other hand, the agents who generally are more willing to accept this type of request are the "Obliging". It is interesting to note that in the simulation environment with 5 agents, the "Avoiding" agents were the ones that most accepted this type of request, even though "Avoiding" had a low concern for others. However, this happens because the formula used to evaluate this type of requests, besides "Concern for others" also considers the agents' "Resistance to change", which in turn is known to be extremely low in the Avoiding. As shown in the 40 agent scenario, the values of G. and P. are quite similar, the existing difference is due to the fact that, in the acceptance formula for this type of requests, "Resistance to change" is considered as part of the agents' behavioral style.

To study the dimension of "Resistance to change" we analyzed the number of requests accepted by the agents of each style of behavior. Table 9 presents data related to the analysis of Resistance to change. The µ[0,1] represents the values obtained in study 1 regarding the dimension of "Resistance to change" in each of the behavior styles. A. represents the average percentage of accepted requests for each style of behavior. P. represents the values of A., standardized on a scale of [0,1], where the sum of all values is equals 1.

Table 9. "Resistance to change" dimension – number of requests accepted by n agents for the 5 behavior styles

			Dominating	Integrating	Obliging	Compromising	Avoiding
		µ[0,1]	0,92	0,54	0,12	0,42	0,10
		G.	0,02	0,15	0,30	0,20	0,31
Resistance to change	5 Agents	A.	2,20%	9,81%	26,88%	14,66%	23,57%
		P.	0,02	0,12	0,34	0,19	0,30
	10 Agents	A.	0,71%	6,18%	11,45%	7,51%	10,19%
		P.	0,01	0,17	0,31	0,20	0,28
	20 Agents	A.	0,45%	2,71%	5,19%	3,39%	5,04%
		P.	0,02	0,16	0,30	0,20	0,30
	40 Agents	A.	0,21%	1,23%	2,45%	1,65%	2,40%
		P.	0,02	0,15	0,30	0,20	0,30

Irrespectively of the calculation the acceptance of any type of requests used in the argumentation-based negotiation model proposed in Joao Carneiro et al. (In Press, 2017), and of having the agents expressing preferences for several alternatives and different criteria, it was verified that, in the long term, the values of G. and P. remain practically the same. The agents presented a resistance to change almost equal to that identified in study 1 for each of the behavior styles.

In order to study the dimension "Activity level" we analyzed the average number of statements and questions made by the agents of each style of behavior during the 100 simulations. Table 10 presents the data related to the analysis of "Activity level". The µ[0,1] represents the values obtained in study 1 regarding the dimension of "Activity level" in each behavior style. G. represents the values µ[0,1] normalized on a scale of [0,1], where the sum of all values equals 1. µ represents the mean number of statements and questions performed by each style of behavior over 100 simulations. The σ represents the standard deviation over 100 simulations. The Min. is the minimum number of interventions performed and the Max. is the maximum number of interventions in the 100 simulations. P. represents normalized values of µ on a scale of [0,1], where the sum of all values equals 1.

Table 10. "Activity level" dimension – number of statements and questions made by n agents for the 5 behavior styles

			Dominating	Integrating	Obliging	Compromising	Avoiding
		μ[0,1]	0,94	0,90	0,23	0,58	0,05
		G.	0,34	0,33	0,08	0,22	0,02
Activity level	5 Agents	μ	3,6	3,28	1,31	2,19	0,65
		σ	1,48	1,82	1,06	1,30	0,71
		Min.	0	0	0	0	0
		Max.	8	9	4	6	2
		P.	0,32	0,29	0,11	0,19	0,05
	10 Agents	μ	3,28	3,41	0,8	1,65	0,59
		σ	1,41	1,50	0,79	1,13	0,69
		Min.	0	0	0	0	0
		Max.	8	9	4	5	3
		P.	0,33	0,35	0,08	0,16	0,06
	20 Agents	μ	2,56	2,56	0,38	0,87	0,18
		σ	1,41	1,52	0,63	0,89	0,41
		Min.	0	0	0	0	0
		Max.	8	9	3	5	2
		P.	0,39	0,39	0,05	0,13	0,02
	40 Agents	μ	1,82	1,54	0,11	0,33	0,05
		σ	1,27	1,21	0,34	0,61	0,24
		Min.	0	0	0	0	0
		Max.	8	7	2	5	2
		P.	0,47	0,4	0,02	0,08	0,01

We have verified that in relation to the dimension of "Activity level" the values of G. and P. were very similar. It is interesting to note that as the number of agents was increased in the various simulation environments, the fact that there were several "Dominating" and "Integrating" agents in the same decision process led to the monopolization of the conversation by them.

To study (h3) we created 2 simulation environments where 5/12 agents sought to achieve consensus. We created groups of 5 simulations where in these 5 simulations each of the 5/12 agents always had the same preferences regarding the alternatives and criteria. In addition, 4/11 agents always maintained the same behavioral style and there was 1 agent (which was the target agent) that in each of the 5 simulations had each of the 5 possible behavior styles (without repetition). The idea was to compare each of the styles of behavior under the same context. Each group of 5 simulations was repeated 20 times, the difference from one group to another being that the agents generated new preferences for alternatives and criteria and the other 4/11 agents adopted a new behavioral styles (randomly). A total of 200 simulations were performed (2*5*20). To understand the impact of the decision on each of the agents, satisfaction was used as a metric, according to Carneiro, Santos, Marreiros, and Novais (In Press, 2017). Satisfaction varies on a scale of [-1,1], where -1 means extremely dissatisfied and 1 means extremely satisfied.

Table 11 shows the average satisfaction and the standard deviation of the target agent using each behavior style in a simulation environment with 5 agents. We found that on average, satisfaction was higher using the "Dominating" behavior style, however, it was also with the "Dominating" behavior style that satisfaction showed the most variability. Through the use of the "Obliging" behavior style, the agent achieved on average the lowest satisfaction but also less variable.

Table 11. Mean and standard deviation of satisfaction with five agents

	Dominating	Integrating	Obliging	Compromising	Avoiding

μ	0,33	0,21	0,19	0,21	0,25
σ	0,54	0,30	0,23	0,29	0,27

Table 12 shows the number of times the target agent achieved more or less satisfaction in each of the groups of 5 simulations with each behavior styles (5 agent). “1st means the highest satisfaction” and “5th” means the lowest satisfaction within each set of 5 simulations. For example, with the Dominating behavior style, the agent was able to achieve 14 times the best satisfaction result in relation to the other behavior styles (under the same conditions). However, the Dominating behavior style also caused the agent to get the worst satisfaction result 6 times. We found that by using the “Integrating” style of behavior in this simulation environment most of the times, the satisfaction obtained was intermediate.

Table 12. Number of times each style appears in the several ranks of satisfaction

	Dominating	Integrating	Obliging	Compromising	Avoiding
1º	14	0	4	1	1
2º	0	2	3	4	11
3º	0	15	2	3	0
4º	0	2	2	10	6
5º	6	1	9	2	2

Figure 15 shows the satisfaction obtained by the target agent in the 5-agent simulation environment using the Dominating and Obliging behavior styles. As we can see, although most of the time the “Dominating” achieves greater satisfaction, when it cannot achieve its goals it is also much more dissatisfied. On the other hand, the “Obliging” shows that its satisfaction throughout the various simulations is more stable.

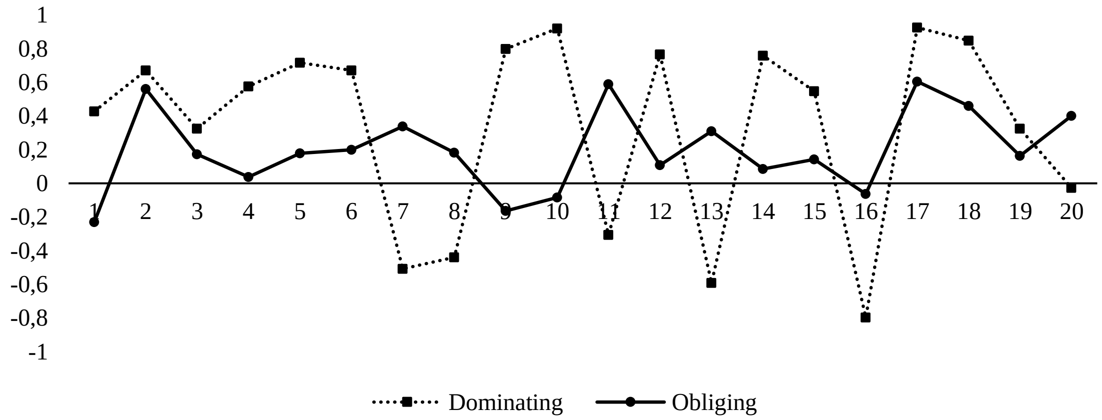

Figure 15. Satisfaction with Dominating and Obliging in 100 simulations

Table 13 shows the average satisfaction and standard deviation of the target agent using each of the behavior styles in a 12 agent environment simulation. It was again verified that the agent with the “Dominating” style continues to achieve the highest average satisfaction, showing also the most variability. With 12 agents, the average satisfaction of “Integrating” was quite close to that of “Dominating” with the advantage of showing much less variability.

Table 13. Mean and standard deviation of satisfaction with 12 agents

	Dominating	Integrating	Obliging	Compromising	Avoiding
μ	0,15	0,11	-0,03	0,09	-0,05
σ	0,47	0,32	0,38	0,36	0,36

Table 14 shows the number of times the target agent achieved more or less satisfaction in each of the 5-simulation groups with each of the behavior styles (12 agents) – “1st” means/refers to the highest satisfaction and “5th” means the lowest satisfaction within each set of 5 simulations.

Table 14. Number of times each style appears in the several ranks of satisfaction

	Dominating	Integrating	Obliging	Compromising	Avoiding
1º	6	4	2	4	4
2º	4	5	3	5	3
3º	2	4	4	6	4
4º	3	4	6	0	7
5º	5	3	5	5	2

Figure 16 presents the satisfaction obtained by the target agent in the 12-agent simulation environment using the Dominating, Obliging and Compromising behavior styles.

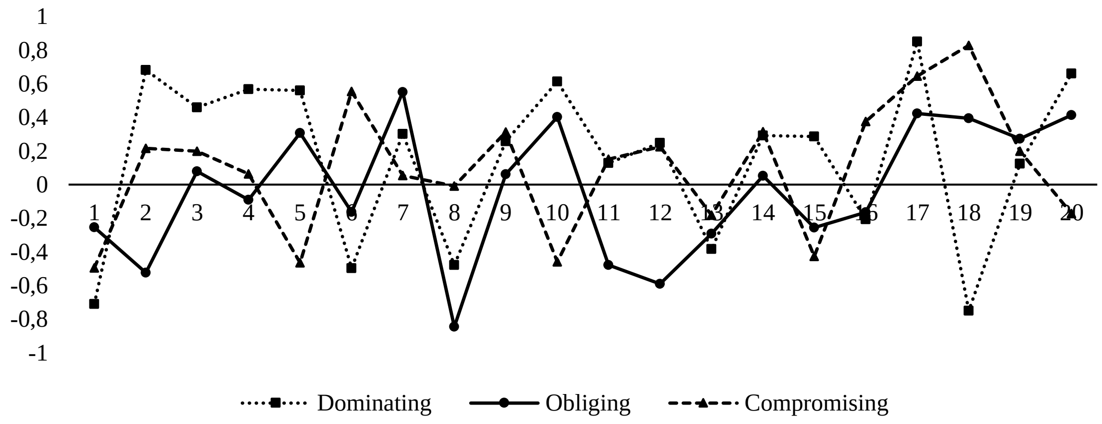

Figure 16. Satisfaction with Dominating, Obliging and Compromising in 100 simulations

7. Discussion

Using agents to represent decision-makers in group decision-making processes is a widely used strategy in our field. The representation of the decision-makers may have different levels of complexity and should be conceived according to the context and objectives of the system that will operate. We must be extremely mindful when designing the representation of decision-makers in group decision support systems that will be used by the decision-makers themselves during the decision process. Let us imagine a decision-maker, who has certain limitations, so that he/she is not able to dialogue with the other decision-makers in a face-to-face meeting. This decision-maker has no persuasive skills and the only influence he/she has in the decision is his/her own vote. If such a decision-maker was literally represented by an agent, he would generate a purely reactive agent, not having any influence in the decision (except for the fact that his/her own preferences would be taken into account). The question that arises is: would this decision-maker be interested in using a system that would represent him/her in this way, mimetizing his unwanted characteristics? This means that this decision-maker may have interest in the process and also knowledge that would add value to the decision-making process, but still could not show it in face-to-face meetings. Thus, the decision-making process would only benefit from representing the decision-maker in a way that he/she is not, or at least in a way he/she cannot be in face-to-face meetings. Moreover, as we have previously asserted, it would be impossible (with the current knowledge) to define a decision-maker in a way that allows him/her to be used in all future meetings. Regardless of the decision make’s personality, due to his/her intentions/goals, the behavior will invariably shift according to his/her interests and context. Rather than a point in time, the decision-making process unfolds over a period of time. It requires several steps such as the exchange of ideas, reflection on the others' opinions, the maturing of ideas, etc. Therefore, the duration of the decision-making process depends on several factors, but what we would like to point out is that the important decisions made in large organizations do not happen over a short period of time. This means that a GDSS will be used throughout the process and it should allow the decision-makers to express different intentions during that same process. All of this led us to focus on defining behavioral styles rather than defining the decision-makers' personality.

The results we obtained with this work were way stronger than we anticipated. However, at this point we consider that although we have verified the hypotheses h2 and h3, the results we achieved still aren't as beneficial as they could be in real scenarios. This happens because of the scarcely human way by which the variables are randomly generated. For example, in our simulations, agents with obliging behavior tend to reach/seek the goals of all other agents, which is a rather unrealistic scenario. In a real situation, an obliging agent will probably seek to achieve the goals of a subgroup of decision makers who, in turn, may even agree with each other. Also, in a real context, decision-makers are able to reconfigure their preferences throughout the process. This can happen (for example) because the decision maker may agree with arguments that support certain opinions and thereby change their preferences.

Another key feature in the development of this work was to verify that no style of behavior is the most or the least advantageous every single time, (which may occur in real situations), making it impossible for decision-makers to think that "it is worth trying to deceive the system" to their own benefit. The idea is that, for decision makers, best results may be achieved by selecting the behavior style that best represents their intentions. Besides demonstrating the interest of selecting a behavior that meets the intentions of decision makers, it helps decision-makers to feel motivated to make a rational choice of the behavioral style. In turn, GDSS may use this information (of what decision makers want) to, by means of algorithms or other strategies, promote consensus and the quality of the decision. In the experiments we ran, we showed that agents configured with the Dominating behavior style tend to reach their goals more often, whilst also being the ones who are the most harmed when they don't succeed.

8. Conclusions and Future Work

Ultimately, with the ever-increasing profusion of large organizations, group decision-making has become the rule in terms of decision format over the last decades. Organizational growth has posed new challenges, namely due to the difficulties experienced by top managers and executives when they need to meet in a same place at the same time. To support decision processes, Web-based Group Decision Support Systems have been widely proposed in literature as means to allow the decision-makers to participate in the decision process anytime and anywhere. The fact that they are web-based makes them multiplatform systems prone to be rendered accessible through almost any kind of device. However, several limitations make it hard for them to succeed, such as: endowing the representation, the interests and intentions of the decision-makers with accuracy.

In this work, we suggested a set of behavior styles that can be used to model agents that can represent decision-makers in the context of group decision-making. Our option renders the agents much more reality-based because, besides allowing the typical configurations related to the problem (alternatives and criteria), it makes them capable of representing the decision-makers' intentions. In this context, we conceive intentions as what the decision-makers wants to get from the decision-making process, i.e., not only what they intend to achieve (objectives) but also how they intend to face them. This means that in our approach, a decision-maker may consider (for instance) Alternative i: a) the best solution for a certain problem and his main intention is to achieve that solution, b) the best solution but his main intention may be to please and meet a subset of decision-makers' interests, or c) in an earlier stage of the decision-making process but, because he considers his position to be less solid and by having little knowledge about the problem, he prefers to remain less interventive until he constructs a more solid and substantiated opinion.

This approach is intended to be used not only in simulators but also in real systems. This raised concerns that normally are not considered in the literature in this field, such as assessing how consensual is the understanding of the proposed behavioral styles and of how people classify them. Since we were able to validate our hypotheses, there are now exact operating values for each behavioral style that from now on, can be used elsewhere. Also, we developed a prototype that allowed us to perceive and interpret the results of using behavioral styles as the basis for modeling agents. We found that using behavioral styles allows the automatic negotiation mechanisms to enjoy the typical heterogeneity of real meetings.

In the future, the use of other models either derived from personality or attachment theory, or possibly both, may open new avenues for agent modeling, with further improvements in the quality of their representativeness. We foresee that these developments may meet the ever-changing needs of decision-makers, that may often be willing to shift from simulating their own traits to change functioning styles to optimize performance in different environments depending on the situation, present or absent he may be. If one can even configure his/her own pattern of changes, then intelligence systems will really keep pace with the complexities and subtleties of human behavior either for purposes of simulation/representation or intended enhancement. These changes may help a system to support group decision-making to perceive important information and to use that same knowledge to support the decision.

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